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LEPROSY CASE MODELING IN EAST JAVA USING SPATIAL REGRESSION WITH QUEEN CONTIGUITY WEIGHTING

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ABSTRACT

Leprosy, a highly contagious disease caused by the bacterium Mycobacterium leprae, can result in permanent disability if left untreated. It remains a significant public health issue in many regions, particularly tropical countries like Indonesia. Despite ongoing control efforts, incidence rates are still high in some areas. In 2023, East Java had the highest number of leprosy cases in Indonesia, with 2,124 out of 7,166. To understand the factors contributing to these cases, this study explores various influences and offers policy recommendations to reduce leprosy in East Java. The study uses spatial modeling with a weighting scheme based on queen contiguity, selected because leprosy spreads through human interactions and movement, creating spatial dependencies. It examines spatial, social, economic, educational, and environmental factors based on cross-sectional data from 38 regencies/cities in East Java for 2023. Among the regression models tested, the spatial error regression model proved most effective, showing an R-Square value of 67.14% and an AIC of 213.023. Key findings identified (X_4) average years of schooling and (X_5) healthcare worker ratios as significant factors influencing leprosy cases. These results aim to guide policymakers in developing stronger leprosy control strategies and offer a basis for further research in East Java.

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1. INTRODUCTION

Infectious diseases remain a serious concern due to their diverse transmission routes, including contact, air, water, food, animals, and vectors [1]. Leprosy, caused by Mycobacterium leprae, is still prevalent in Indonesia, with cases increasing from 2021 to 2022 [2]. In 2023, East Java reported Indonesia's highest leprosy case count, comprising 2,124 of the country's 7,166 total cases [3]. The main challenge in East Java is limited public awareness of leprosy. Although the government has implemented outreach, surveillance, chemoprophylaxis, and comprehensive management strategies [4]. However, despite these efforts, leprosy cases may still exhibit spatial clustering, where cases in one area correlate with cases in neighboring areas. Understanding these spatial patterns is crucial, as they can indicate underlying environmental, social, or behavioral factors that are geographically influenced. Several techniques can be applied to analyze such spatial effects that account for spatial influence in regression analysis. These methods consider the impact of spatial location on both dependent and independent variables and include Spatial Autoregressive Regression (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), Geographically Weighted Regression (GWR), and Multiscale Geographically Weighted Regression (MGWR) [5]. This study uses spatial regression with queen contiguity weighting to examine key factors affecting the prevalence of leprosy cases in East Java. Spatial regression was employed in this study because the distribution of leprosy cases in East Java shows spatial autocorrelation, indicating that neighboring areas influence the incidence in one location. A queen contiguity spatial weight matrix was used to model these spatial relationships, as it captures connections between districts that share either a border or a corner point. This method is considered the most appropriate for complex administrative regions and more accurately reflects the potential spread of disease across geographical boundaries.

Several studies have linked environmental and socioeconomic factors to leprosy incidence. Winarsih et. al [6], used Chi-Square and spatial analysis to associate poverty and population density with leprosy in Jepara. Andreas et. al. [7] applied GWR and found shared sanitation facilities and poverty influenced cases in East Java. Noviani et. al. [8] using GWPR, identified factors such as healthy living practices, doctor availability, and education levels affecting cases in Central Java. Aipassa et. al. [9] found healthcare worker numbers significantly impacted leprosy in Maluku using negative binomial regression.

Building on these, this study applies spatial regression with queen contiguity weighting to analyze 38 regencies/cities in East Java using 2023 data. Unlike prior research that often used descriptive or non-spatial methods, this approach captures spatial autocorrelation where neighboring areas influence each other using a queen contiguity matrix that reflects both border and corner connections [10]. A hallmark of spatial modeling is the presence of a weighting matrix that marks relationships between one region and another [11]. This method enhances accuracy in identifying key regional factors driving leprosy cases and provides better support for targeted policy interventions. The novelty of this research lies in its advanced spatial analysis, focus on spatial dependency, and use of the most recent data to support more precise and location-specific public health strategies [12]. This study improves previous methods by accounting for spatial autocorrelation, recognizing that leprosy transmission is influenced by interactions across neighboring regions. By integrating spatial relationships, it provides a deeper understanding of how regional social, economic, educational, and environmental factors affect case distribution. Using 2023 data adds relevance, enabling more accurate, area-specific policy recommendations. The novelty lies in applying advanced spatial analysis with recent data to address leprosy as a pressing public health issue.

2. RESEARCH METHODS

2.1 Research Data and Types of Research

This study relies on secondary data acquired from the Central Statistics Agency or Badan Pusat Statistik (BPS) in 2023. The data analyzed includes leprosy cases in 38 regencies/cities in East Java in 2023 and is cross-sectional, with each regency/city serving as an observation subject. The data structure includes response and predictor variables, with the response variable (Y) is the percentage of leprosy cases, while the predictor variables (X) consist of population density (X_1), the percentage of households with access to adequate sanitation (X_2), the percentage of impoverished residents (X_3), average years of schooling (X_4), and the healthcare worker ratio (X_5). All variables are continuous and measured on a ratio scale, allowing for comprehensive statistical analysis to understand the factors influencing leprosy cases in each regency/city in East Java. The OLS model does not account for spatial dependencies between regions. To address this, spatial regression models are employed, incorporating a spatial weighting matrix ($\mathbf{W}$) to capture the relationships between neighboring regions.

2.2 Leprosy Case

Leprosy is a chronic infectious disease caused by *Mycobacterium leprae*, mainly targeting the peripheral nerves and skin [13]. Leprosy may be transmitted by inhaling droplets with M. leprae bacteria or through sustained skin contact with someone who is infected [14]. This disease can cause disability in humans if early detection and timely treatment are unavailable. This is because the skin, nerves, limbs, and eyes of a person with leprosy will undergo progressive and irreversible damage [15]. Thus, The World Health Organization (WHO) promotes early diagnosis and multidrug therapy (MDT) as key strategies for leprosy control [16].

2.3 Data Analysis Technique

The data collected were analyzed using the spatial regression method to examine the relationship between dependent and independent variables while considering spatial or regional factors. Classical assumption and spatial effect tests are required in spatial regression modeling. Classical assumption tests include normality and multicollinearity tests. In contrast, spatial effect tests include spatial autocorrelation, spatial heteroscedasticity, and spatial dependence tests [17]. This research applies spatial data analysis by comparing the classical regression, spatial error, and spatial lag methods using Queen Contiguity weighting.

2.4 Research Procedure and Data Analysis

The process of analyzing data in this study is structured as follows:

2.4.1 Description of Leprosy Case Factors in Thematic Map

a. Input leprosy case data for East Java, along with predictor variables or factors that may influence it using Microsoft Excel software.

b. Load the East Java thematic map in SHP format into GeoDa 1.20 software.

c. Use the Merge Table feature in GeoDa 1.20 to export leprosy case data in East Java and its predictor variables.

d. Classify leprosy cases and their predictor variables in East Java by regency or city.

e. Use the Custom Breaks Map option to display the classification of leprosy cases and predictor variables in East Java, selecting Natural Breaks Map in the Breaks option.

f. Generate the output from the thematic map showing leprosy cases and predictor variables across each regency and city in East Java.

2.4.2 Modeling the Leprosy Cases in East Java

a. Input the data on leprosy cases in East Java along with the potential predictor variables using Microsoft Excel.

b. Input the leprosy case data for East Java and the variables believed to influence it by exporting the information from GeoDa 1.20 software.

c. Incorporate a weighting matrix to model leprosy cases in East Java by creating it in GeoDa 1.20 through the following steps:

   i. Construct a spatial weighting matrix by selecting the concept of Queen Contiguity. Queen contiguity, or intersection, is derived from a combination of Rock Contiguity and Bishop Contiguity. This weighting matrix illustrates an area in relation to neighboring regions where sides and angles intersect [18]. The Queen Contiguity weighting matrix assigns a binary code of 1 to regions where sides or angles intersect and a binary code of 0 to regions where they do not.

ii. Generate summary results, specifically the connectivity map for each regency or city based on the weights obtained.

d. Conduct a multicollinearity assumption test by calculating the VIF (Variance Inflation Factor) for each independent variable, using the VIF calculation formula [19]:

$$VIF = \frac{1}{1 - {R_j}^2} \tag{1}$$

If the VIF value is below 10, it indicates that multicollinearity is absent [20], allowing the analysis to proceed to the subsequent test.

e. Estimate the parameters from the linear regression analysis of the leprosy cases in East Java, using the classical regression model equation [21]:

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \varepsilon_i \,; i = 1,2,\ldots,n \tag{2}$$

f. Perform spatial effect tests; if spatial effects are present, employ spatial regression methods to model the leprosy cases in East Java. This test is conducted using the Moran Index Test and Breusch-Pagan test [22].

i. Moran Index Test

The formula for calculating the Moran Index using a not-standardized spatial weighting matrix:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} * (x_j - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{n} (x_j - \bar{x})} \tag{3}$$

as well as the formula using a standardized spatial weighting matrix:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_j - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_j - \bar{x})^2} \tag{4}$$

If the $p - value \geq \alpha$ and the test statistic value is $|Z(I)| \leq z(\alpha/2)$, the null hypothesis is not rejected, and the conclusion is that there is no significant spatial autocorrelation [23].

ii. Breusch-Pagan Test

Perform the Breusch-Pagan (BP) test to evaluate spatial heterogeneity. The statistics for the Breusch-Pagan (BP) test are as follows:

$$BP = \frac{1}{2} f^T Z (Z^T Z)^{-1} Z^T f + \left(\frac{1}{T}\right) \left[\frac{e^T W e}{\sigma^2}\right]^2 \sim \chi^2{}_{(p+1)} \tag{5}$$

If the $p - value \geq \alpha$ (0.05) and the test statistic value $\leq \chi^2_{(\alpha;x)}$, the null hypothesis is not rejected, indicating that there is no significant evidence of spatial heterogeneity within the model [24].

g. Determine the parameters of the spatial regression model by utilizing the findings from the spatial effect tests on leprosy cases in East Java, applying the general spatial regression equation [25].

$$\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{u} \tag{6}$$

$$\boldsymbol{u} = \boldsymbol{\lambda} \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\varepsilon} \tag{7}$$

The weighting matrix **W** is an $n \times n$ matrix used for measurement.

h. Estimate the parameters of the spatial lag model considers the dependent variable $\boldsymbol{y}$ influenced by neighboring values through spatial dependence (spatial lag).

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{u} \tag{8}$$

The spatial lag coefficient ρ measures the degree of spatial dependency and significant ρ suggests that the values of y are spatially dependent.

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{u} \tag{9}$$

$$\boldsymbol{u} = \boldsymbol{\lambda}\boldsymbol{W}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{10}$$

The spatial error coefficient $\boldsymbol{\lambda}$ represents spatial dependence in the error terms and significant $\boldsymbol{\lambda}$ suggests spatial autocorrelation in the residuals, which means unexplained variation might be influenced by spatial factors.

i. Estimate the parameters of the spatial error model focuses on spatial correlation in the error term $\boldsymbol{u}$ rather than in the dependent variable.

j. Perform individual tests to evaluate the effect of each predictor variable on the response variables through spatial lag models and spatial error models.

k. Execute Likelihood-Ratio Test (LRT) for model fit assessment. The LRT test statistics are formulated as follows [26]:

$$LRT = -2ln\lambda \tag{11}$$

The value of λ is indicated below:

$$\lambda = \frac{L(\Omega_0)}{L(\Omega_1)} \tag{12}$$

If the LRT $> \chi^2_{(\alpha;x)}$, the conclusion is that the model is appropriate and the next steps can be carried out [27].

l. Assess the accuracy of spatial regression models by calculating the R^2 and AIC (Akaike Information Criterion) values [28].

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{13}$$

$$AIC = -2Lm + 2m \tag{14}$$

m. Compare the R^2 and AIC values of the three models; the model with the highest R^2 and the lowest AIC is the best model to use [20].

n. Interpret the outcomes of the linear regression analysis of the leprosy case data for East Java and the factors believed to influence it in 2023.

3. RESULTS AND DISCUSSION

3.1 The Distribution of Leprosy Cases in East Java

According to the 38 districts/cities in East Java, the spread of leprosy in East Java is depicted in the thematic map below.

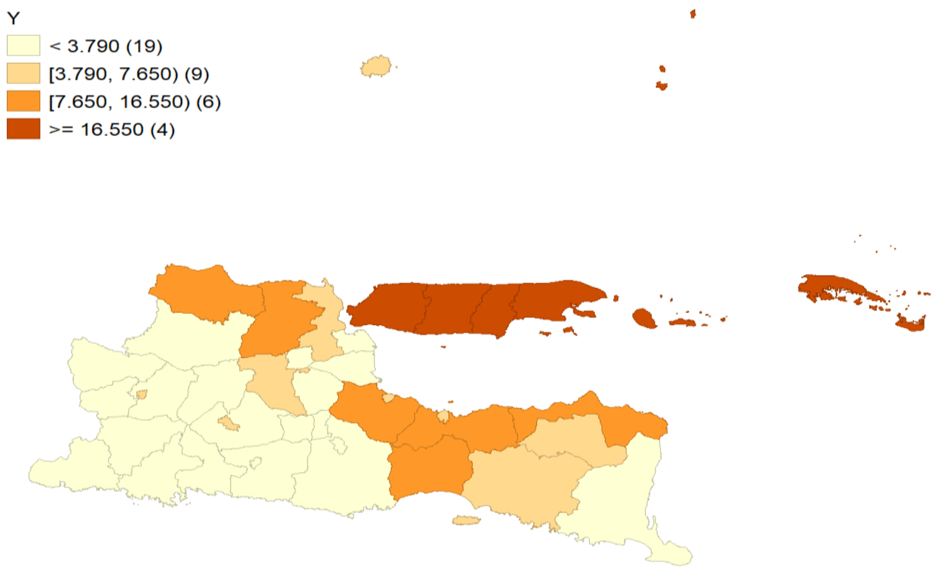

Figure 1. Thematic Map of Leprosy Cases Distribution in East Java in 2023

Based on Figure 1, the thematic map showing the distribution of leprosy in East Java illustrates the number of cases divided into four categories. Areas with the highest case category (≥16,550 cases) are indicated in dark brown, including Sumenep, Sampang, Pamekasan, and Bangkalan on Madura Island, which require intensive management. Areas classified as medium to high (7,650 – 16,550 cases) are colored dark orange, such as Probolinggo, Situbondo, Bondowoso, Jember, Tuban, Jombang, and several other regions that need special attention for control and prevention. In the moderate category (3,790 – 7,650 cases), regions marked in light orange include Banyuwangi, Lumajang, Pasuruan, Malang, Lamongan, Gresik, Mojokerto, Bojonegoro, Madiun, and Magetan. Continuous monitoring is still necessary in these areas to prevent increased cases. Finally, the lowest case category (<3,790 cases) is indicated in bright yellow, scattered across Pacitan, Ponorogo, Trenggalek, Tulungagung, Blitar, Kediri, Nganjuk, Sidoarjo, Surabaya, Ngawi, Kediri City, Blitar City, Malang City, Pasuruan City, Probolinggo City, and Madiun City. Areas in this category show that the spread of leprosy cases is relatively low, indicating the effectiveness of disease control in those regions. The map shows that the Madura region, the eastern part (such as Probolinggo, Situbondo, Bondowoso), and the northern part of East Java have higher cases. At the same time, the lighter-colored areas indicate better effectiveness in disease control. According to the analysis of the thematic map showing leprosy distribution in East Java, it is known that there is a discrepancy in the number of cases across various regions. A statistical analysis approach was conducted to understand the factors influencing this variation.

3.2 Multicollinearity Test

The multicollinearity test aims to detect any correlation among independent variables in a regression model. In a classical regression approach, the initial step involves conducting a multicollinearity test, which was assessed using the VIF value criterion in this study. A VIF value below 10 indicates no multicollinearity. The outcomes of the multicollinearity test are shown in Table 1.

Table 1. VIF Values for Each Independent Variable

Variable	Variable Description	VIF	Results
X_1	Population Density	3.285	No indication of multicollinearity
X_2	Percentage of Households with Access to Adequate Sanitation	2.543	No indication of multicollinearity
X_3	Percentage of Impoverished Residents	3.313	No indication of multicollinearity
X_4	Average Years of Schooling	8.421	No indication of multicollinearity
X_5	Healthcare Worker Ratio	1.301	No indication of multicollinearity

Based on Table 1, the VIF values of the five variables are below 10. Thus, it can be concluded that there is no multicollinearity, and the analysis can proceed to the next stage.

3.3 Modeling Leprosy Cases in East Java Using Classical Regression

The process involves the following stages in modeling leprosy cases in East Java using a classical regression approach.

3.3.1 Estimation and Parameter Testing of the Classical Regression Model

The next step is to conduct the estimation using the classical regression model, with the results presented in **Table 2**.

Table 2. Classical Model Estimation

Parameter	Estimated Value
β_0	9.08937
β_1	0.00124
β_2	-0.06586
β_3	-9.01192
β_4	0.87150
β_5	-1.06065

From **Table 2**, the outcomes of the classical regression model estimation for the data are as follows.

$$\hat{Y}_i = 9.8937 + 0.00124X_{i,1} - 0.06586X_{i,2} - 9.01192X_{i,3} + 0.87150X_{i,4} - 1.06065X_{i,5};$$
$$i = 1,2,3,\dots,38$$

Next, a simultaneous test was conducted to determine whether all predictor variables have a significant effect on leprosy cases in East Java as the response variable. A p-value of was obtained. P-value is 0.0000099. If $\boldsymbol{\alpha} = 0.05$, then p-value $< \boldsymbol{\alpha}$. In addition, $\boldsymbol{F_{count}}$ is 9.4951 and $\boldsymbol{F}_{(\mathbf{0.05;5;32})}$ or $\boldsymbol{F_{Table}}$ is 2.51. It's mean that $\boldsymbol{F_{count}} > \boldsymbol{F_{Table}}$. As a result, it can be concluded that the five predictor variables collectively influence leprosy cases in East Java. Following the simultaneous test, an individual test is required to assess the significance of each predictor variable's effect on the response variable, which is leprosy cases in East Java. The individual test results for the classical regression model are provided in **Table 3**.

Table 3. Individual Test Results of Classical Regression Models

Parameter	T-Statistics	P-Value	Information
β_0	0.94352	0.35248	Failed to Reject H_0
β_1	2.393	0.02275	Reject H_0
β_2	-0.77424	0.44447	Failed to Reject H_0
β_3	-0.30983	0.75870	Failed to Reject H_0
β_4	3.18353	0.00323	Reject H_0
β_5	-0.93269	0.35796	Failed to Reject H_0

Table 3 shows that two predictor variables significantly impact the response variable, namely population density and average years of schooling.

3.3.2 Goodness of Fit for the Classical Regression Model

The goodness of fit for a classical regression model is assessed through the coefficient of determination R^2 and the Akaike Information Criterion (AIC). These values are commonly used metrics to evaluate the suitability of the applied regression model. The classical regression model yielded an R^2 value of 0.603703, indicating that 60.37% of the predictor variables account for the variation in the response variable, with an AIC value of 217.773.

3.4 Spatial Effect Test

There are two tests that need to be conducted in the spatial effect analysis: the spatial dependency and heterogeneity test.

3.4.1 Spatial Dependency Test

The Moran's Index is a method used in spatial analysis to assess the spatial relationships within a given area. Based on the results of the spatial dependency test, the p-value is 0.00711. If α = 0,05, then the p-value $< \alpha$. The test statistic for Moran's Index $|Z(I)|$ is 2.6915. If $z(\alpha/2)$ or z_{Table} is 1.960. It's mean that $Z(I) > z(\alpha/2)$. Thus, the determination is to reject H_0 and the conclusion indicates the presence of spatial autocorrelation, showing that leprosy cases in one area are influenced by cases in neighboring areas.

3.4.2 Spatial Heterogeneity Test

Based on the heterogeneity test, the results for the classical model, lag model, and error model are presented in Table 4.

Table 4. Heterogeneity Test

Breusch-Pagan Test	Statistic Value	P-Value	Information
Classical Model	11.6204	0.03451	Reject H_0
Spatial Lag Model	12.9874	0.03719	Reject H_0
Spatial Error Model	12.2871	0.04816	Reject H_0

Based on Table 4, it is known that for the classical model, the p-value is 0.03451. The classical BP value is 1.6204. For the spatial lag model, the p-value is 0.03719 and the BP lag value is 12.9874. For the spatial error model, the p-value is 0.04816, and the BP error value is 12.2871. If α = 0,05, then the p-value $< \alpha$ and if $\chi^2_{(0.05;5)}$ or χ^2_{Table} is 11,070, it's mean that BP value $> \chi^2_{(0.05;5)}$ or χ^2_{Table}. Based on the obtained p-values and Breusch-Pagan statistics, the decision is to reject H_0, concluding that there is spatial heterogeneity in the classical, spatial lag, and spatial error models.

3.5 Modeling Leprosy Cases in East Java using Spatial Lag Regression

In the modeling analysis of leprosy cases in East Java for 2023 using a spatial lag regression method, the process will follow these specific stages.

3.5.1 Estimation and Suitability Test of the Spatial Lag Regression Model

The first step in modeling with the spatial lag model begins with estimation. The parameter estimation results of the spatial lag model for leprosy cases in East Java are shown in Table 5.

Table 5. Parameter Estimation of the Spatial Lag Regression Model

Parameter	Estimated Value
$\hat{\rho}$	0.377838
β_0	7.07688
β_1	0.00103872
β_2	-0.0405304
β_3	-0.679569
β_4	0.852391
β_5	1.35158

From Table 5, the results for the parameter estimator of the spatial lag model for leprosy cases in each district/city in East Java are as follows.

$$\hat{Y}_i = 0.377838\, \boldsymbol{W_i Y} + 7.07688 + 0.00103872\, X_{i,2} - 0.0405304\, X_{i,2} - 0.679569\, X_{i,3} + 0.852391\, X_{i,4} - 1.35158\, X_{i,5};\ i = 1,2,\ldots,38$$

The next test is model fit test for the spatial lag model, which yielded a p-value is 0.04661. If α = 0.05, then the p-value $< \alpha$. Likelihood ratio test (LRT) value is 3.9594. If $\chi^2_{(0.05;5)}$ or χ^2_{Table} is 3.481. It's mean that LRT value $> \chi^2_{(0.05;5)}$. Therefore, the decision is to reject H_0 , concluding that the spatial lag model is appropriate and the subsequent steps can be carried out.

3.5.2 Individual Testing of the Spatial Lag Regression Model

Following the completion of the model fit test, it can then proceed to the next step, which is the individual test of the spatial lag regression model, as shown in **Table 6**.

Table 6. Individual Test of the Spatial Lag Regression Model

Parameter	Z-Score	P-Value	Information
$\hat{\rho}$	2.01535	0.04387	Reject H_0
$\hat{\beta}_0$	0.806084	0.42019	Failed to Reject H_0
$\hat{\beta}_1$	2.30993	0.02089	Reject H_0
$\hat{\beta}_2$	-0.546895	0.58445	Failed to Reject H_0
$\hat{\beta}_3$	-0.0269904	0.97847	Failed to Reject H_0
$\hat{\beta}_4$	3.55755	0.00037	Reject H_0
$\hat{\beta}_5$	-1.37914	0.16785	Failed to Reject H_0

Based on **Table 6**, it is shown that the variables significantly affecting leprosy cases in East Java are population density (X_1) and the percentage of the poor population (X_4).

3.5.3 Goodness of Fit for the Spatial Lag Regression Model

From the spatial lag modeling conducted, a R^2 value of 0.650829 was obtained, indicating that 65.08% of the predictor variables contribute to explaining the variation in the response variable, with an AIC value of 215.813.

3.6 Modeling the Leprosy Cases in East Java Using Spatial Error Regression

We used the spatial error regression method to analyze leprosy cases in East Java for 2023, progressing through the stages outlined below.

3.6.1 Estimation and Suitability Test of the Spatial Error Regression Model

The spatial error model will be the next to be applied, starting with the estimation phase. The parameter estimate results are outlined in **Table 7**.

Table 7. Parameter Estimation of the Spatial Error Regression Model

Parameter	Estimated Value
β_0	0.593894
β_1	0.0008473
β_2	-0.0215953
β_3	-4.95846
β_4	0.622185
β_5	-1.92105
λ	0.593894

Based on **Table 7**, the results for the parameter estimates of the spatial error model for leprosy cases in each district/city in East Java are as follows.

$$\hat{Y}_i = 0.593894 + 0.0008473\, X_{i,1} - 0.0215953\, X_{i,2} - 4.95846\, X_{i,3} + 0.622185\, X_{i,4} - 1.92105\, X_{i,5};$$
$$i = 1,2,\dots,38$$

In the model fit test, the results indicate that the spatial error model has a p-value is 0.02932. If $\alpha = 0.05$, then the p-value $< \alpha$. Likelihood ratio test (LRT) value is 4.7488. If $\chi^2_{(0.05;5)}$ or χ^2_{Table} is 3.481. It's mean that LRT value $> \chi^2_{(0.05;5)}$. Therefore, the decision is to reject H_0, concluding that the spatial error model is appropriate and the subsequent steps can be carried out.

3.6.2 Individual Testing of the Spatial Error Regression Model

After finishing the model fit test, the following step is to conduct the individual test for the spatial lag regression model, as outlined in **Table 8**.

Table 8. Individual Test of the Spatial Error Regression Model

Parameter	Z-Score	P-Value	Information
$\hat{\beta}_0$	1.57156	0.11605	Failed to Reject H_0
$\hat{\beta}_1$	1.95212	0.05092	Failed to Reject H_0
$\hat{\beta}_2$	-0.277706	0.78124	Failed to Reject H_0
$\hat{\beta}_3$	-0.214969	0.82979	Failed to Reject H_0
$\hat{\beta}_4$	2.44415	0.01452	Reject H_0
$\hat{\beta}_5$	-2.089	0.03671	Reject H_0
λ	3.30639	0.00095	Reject H_0

Table 8 shows that the variables significantly affecting leprosy cases in East Java are the percentage of the average years of schooling (X_4) and the healthcare worker ratio (X_5).

3.6.3 Goodness of Fit for the Spatial Error Regression Model

From the spatial error modeling conducted, a R^2 value of 0.671410 was obtained, indicating that 65.08% of the variation in the response variable is attributable to the predictor variables, with an AIC value of 213.023.

3.7 Best Model Selection

To identify the best model, one can assess the model with the highest $\boldsymbol{R^2}$ value and the lowest AIC value among the different regression models analyzed. A comparison of the top models from the classical regression, spatial lag model, and spatial error model is shown in **Table 9**.

Table 9. Best Model Selection

Model	R^2	AIC
Classical Model	60.37%	217.773
Spatial Lag Model	65.08%	215.813
Spatial Error Model	**67.14%**	**213.023**

Based on **Table 9**, it is apparent that the spatial error model has the highest R^2 value and the lowest AIC value, which has a R^2 value of 67.14% and an AIC value of 213.023. To conclude, the spatial error model is the most efficient regression model for analyzing leprosy case data in East Java for 2023, as demonstrated by the following equation.

$$\hat{Y}_i = 0.593894 + 0.0008473\, X_{i,1} - 0.0215953\, X_{i,2} - 4.95846\, X_{i,3} + 0.622185\, X_{i,4} - 1.92105\, X_{i,5};\\ i = 1,2,\ldots,38$$

3.8 Best Model Interpretation

The research outcomes suggest that the spatial error model is the best. The interpretation indicates that if the population density in a specific district or city in East Java increases by one unit, the number of leprosy cases in that district or city is expected to rise by 0.008473 units, assuming other predictor variables remain constant. This result aligns with the fact that leprosy spreads through prolonged contact with infected individuals, particularly via droplets from the nose or mouth. In areas with high population density, interactions among individuals occur more frequently, increasing leprosy transmission risk [29].

Additionally, for each increase in the percentage of households with access to adequate sanitation in a particular district or city in East Java, the leprosy cases in that region decrease by 0.0215953 units, assuming other predictor variables remain constant. Leprosy is more prevalent in settings with insufficient access to WASH (water, sanitation, and hygiene). It is commonly linked to simultaneous schistosomiasis infections, as immune responses triggered by schistosomiasis may enhance susceptibility to leprosy [30]. Adequate sanitation is generally accompanied by a cleaner environment that is less contaminated with pathogens and contributes to an overall reduction in the risk of infection, including leprosy. A clean environment can enhance the population's health conditions and strengthen the immune system, thereby reducing the likelihood of contracting infectious diseases.

Furthermore, for each unit increase in the ratio of healthcare workers in a specific district or city in East Java, the number of leprosy cases in that area is expected to decrease by 4.95846 units, assuming other predictor variables remain constant. This result is consistent with the research by [31]. The shortage of professionals in areas such as medicine, nursing, laboratory science, and environmental health poses a serious risk to the health and well-being of individuals, families, and communities, especially those at risk and without adequate resources for self-protection. This suggests that boosting the number of healthcare workers could help decrease the prevalence of such diseases, including leprosy.

Additionally, for each increment in the percentage of the poor population in a particular district or city within East Java, the incidence of leprosy cases in that area is expected to rise by 0.622185 units, assuming other predictor variables remain constant. Research by [32] reveals that respondents with low incomes (below the minimum wage in Surabaya) are 5.2 times more likely to contract leprosy compared to those with higher incomes (above the minimum wage in Surabaya). Other contributing factors include limited access to healthcare services due to financial constraints, geographic distance, and inadequate infrastructure.

Lastly, for each unit enhancement in the average years of schooling in a specific district or city in East Java, the number of leprosy cases in that area is expected to decrease by 1.92105 units, assuming other predictor variables remain constant. Higher education is generally associated with better knowledge of health practices, hygiene, and disease prevention. Leprosy often carries a strong social stigma. Higher education helps individuals understand that leprosy is a treatable disease with appropriate medication rather than a curse or a result of other myths. Education aids in reducing stigma, encouraging those affected to seek treatment sooner, thereby decreasing the risk of further transmission.

4. CONCLUSIONS

Overall, this thematic map illustrates that the regions with the highest leprosy cases (≥ 16,550 cases) are primarily located on Madura Island, specifically in Sumenep, Sampang, Pamekasan, and Bangkalan. These areas require intensive intervention to manage the disease's spread. Furthermore, regions in the eastern and northern parts of East Java, such as Probolinggo, Situbondo, Bondowoso, Jember, Tuban, and Jombang, fall into the medium to high category (7,650 – 16,550 cases), warranting special attention for ongoing control and prevention efforts. Regions with moderate cases (3,790 – 7,650 cases) include Banyuwangi, Lumajang, Pasuruan, Malang, and others, indicating that sustained monitoring is necessary to prevent increased cases. Conversely, areas with the lowest case counts (< 3,790 cases), such as Pacitan, Ponorogo, Trenggalek, and major cities like Surabaya, reflect the success of interventions that have effectively controlled the disease's spread. This suggests that well-implemented control and prevention strategies can produce favorable outcomes in reducing leprosy cases in these regions. Based on the modeling conducted, which includes the classical, spatial lag, and spatial error model, the spatial error model proved to be the most suitable, achieving the highest R^2 value and the lowest AIC value of 67.14% and 213.023, respectively. Additionally, two significant variables affecting leprosy cases in East Java in 2023 are the average years of schooling (X_4) and the healthcare-worker ratio (X_5).

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